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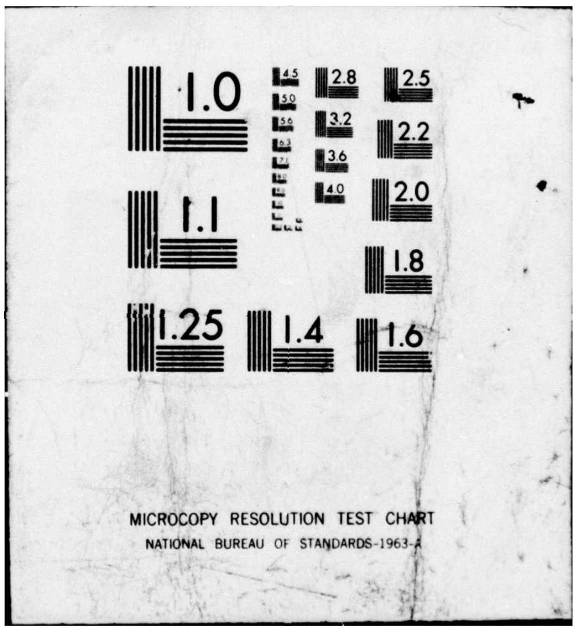
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SIMULATION OF ADAPTIVE CONTROL BY

INSTRUMENTAL-VARIABLE IDENTIFICATION

A. T. Touchstone
A. B. Corripio
Department of Chemical Engineering
Louisiana State University
Baton Rouge, Louisiana 70803

ABSTRACT

This paper presents the use of computer simulation to test the application of the instrumental-variable method of process identification to the adaptive temperature control of a chemical reactor. The method is shown to be stable when used in a closed-loop configuration to update the parameters of a discrete linear model of the reactor. The updated parameters are used to adjust the parameters of a feedback control algorithm. Dynamic information is generated by aperiodic changes in control set-point. Unmeasured disturbances are shown to deteriorate the parameter estimates, but without catastrophic effects.

INTRODUCTION

Today, with the aid of an on-line digital computer, it is possible to use an empirical model to represent a non-linear plant in a sequential manner. Specifically, a low-order linear model is selected to represent the dynamic system. By use of the proper estimation algorithm, the computer is able to produce updated parameter estimates for the empirical model at each sample instant. With this quasi-linearization procedure it is now feasible for the engineer to characterize the dynamics of his process sufficiently to be able to apply such advanced control techniques as the self-adaptive strategy. Because self-adaptive process control is a relatively untried concept, a number of questions must be answered before the technique can be even considered for field implementation. Computer simulation offers a safe and relatively unexpensive approach to obtaining the answers. This paper is an attempt to demonstrate its usefulness.

DEFINITION OF THE PROBLEM

The jacketed stirred-tank chemical reactor shown in Figure 1 is adapted from an example presented by Chiu [1]. The equations describing this system are shown in Table I and were derived by making unsteady-state mass balance on the reactant, and energy balances on the reacting mixture and the jacket. This dynamic model is subject to the assumptions of perfect mixing, constant physical properties, constant holdup volumes and heat transfer coefficient, and negligible heat losses. The values of the model parameters used in the simulation are given in Table II.

A feedback controller is used to modulate the rate of cooling water to the jacket so as to maintain the reactor temperature at its set-point or desired value. Because the reactor is highly nonlinear, adjustment of the controller parameters to achieve acceptable control at one operating level does not guarantee acceptable control at other levels. Variations in reactant rate, inlet temperature and temperature set-point cause the dynamic characteristics of the reactor to change. Hence the need for adaptive control.

THE DISCRETE LINEAR MODEL

In practice, the nonlinear model equations presented in Table I, and the parameter values of Table II are either unavailable or too complex for use in controller design. Even this simplified model must be linearized since the most common controller design methods are based almost exclusively on linear models. In addition, the common proportional-integral (PI) and proportional-integral-derivative (PID) controllers used in industry are based on first and second order models, respectively [2].

Since the identification and control methods studied here are usually implemented on digital control computers, the most convenient model is a difference equation relating plant output (temperature) to input (cooling water rate). The second-order equation used here is of the form:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + b_1 u_{t-M-1} + b_2 u_{t-M-2} + C \qquad (1)$$

where $y = T_R - \overline{T}_R$
$u = W_c - \overline{W}_c$

Note that the linearized nature of the model demands that the input and output variables be expressed in terms of deviations from some operating values, denoted by $\overline{T}_R$ and $\overline{W}_c$. The constant parameter C is included to account for nonzero-mean unmeasured disturbances and for the shifting of the operating point from the initial values. In general, best results are obtained when C is small.

Since the second-order model is selected for use as an empirical representation of the reactor, the only

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other a priori information necessary is the dead time (transportation lag or time delay) parameter M. Although the reactor is a lumped system with no dead time, model fit can be improved by allowing some pseudo-dead time to account for the fact that a second-order equation is used to model a higher (third) order system. In this case a dead-time equal to the sample time of one minute was chosen, based on the open-loop response of the simulated reactor.

ESTIMATION BY INSTRUMENTAL VARIABLE

A detailed discussion of Instrumental Variable regression is the subject of a previous presentation by these authors [3]. This method is chosen to estimate the parameters of Equation 1 because it maintains the simplicity of least-squares regression while avoiding estimation bias due to measurement noise.

Equation 1 can be written in the following vector form:

$$y_t = \phi x_{t-1} \tag{2}$$

where $\phi = [a_1 a_2 b_1 b_2 C]$

$x^T_{t-1} = [y_{t-1} y_{t-2} u_{t-M-1} u_{t-M-2} 1]$

Because the measured output of the plant, y, is corrupted by measurement noise, the presence of past values of the output in the vector of exogenous variables, x, causes bias on the least-squares estimates of the model parameters. This bias is minimized by generating a vector of instruments, containing the output of the model equation:

$$\xi_t = \hat{\phi} z_{t-1} \tag{3}$$

where $z^T_{t-1} = [\xi_{t-1} \xi_{t-2} u_{t-M-1} u_{t-M-2} 1]$

The vector of parameter estimates, $\hat{\phi}$, is then computed by the following recursive formulas:

$$\hat{\phi}_{t+1} = \hat{\phi}_t + (y_{t+1} - \hat{\phi}_t x_t)[1 + z_t^T P_{t/t-1} x_t]^{-1} z_t^T P_{t/t-1} \tag{4}$$

$$P_{t/t-1} = P_{t-1} + D \tag{5}$$

$$P_t = P_{t/t-1} - P_{t/t-1} x_t [1 + z_t^T P_{t/t-1} x_t]^{-1} z_t^T P_{t/t-1} \tag{6}$$

where $P_{t/t-1}$ is the projection of the weighting matrix P at time t, based on observations up to and including y_{t-1}, and D is a lower bound on P. Matrix D controls the parameter tracking capability of the IV estimator. If D = 0, matrix P decreases with time until, eventually, new samples have little effect on the parameter estimates. Each nonzero term of D sets a lower bound on the corresponding term of P, allowing the algorithm to track parameter variations. Matrix D is usually chosen to be diagonal, with each diagonal term corresponding to a different model parameter.

CLOSED-LOOP ESTIMATION

Closed-loop estimation studies were performed for the simple feedback control loop with a PID controller and for the adaptive control configuration employing a Dahlin synthesis controller [4]. The reactor in the closed-loop configuration was forced with a square-wave signal on the set point of the temperature controller.

The PID control algorithm is given by the equation [5]:

$$u_t = u_{t-1} + K_c[e_t - e_{t-1} + \frac{T}{T_i} e_t + \frac{T_d}{T}(e_t - 2e_{t-1} + e_{t-2})] \tag{7}$$

where $e_t = R_t - y_t$

The controller parameters given by Chiu [6] for this reactor are: $K_c = -632.6$ lbs/min-°F, $T_i = 20.9$ min, $T_d = 1.8$ min.

ADAPTIVE CONTROL

For adaptive control, the Dahlin algorithm [4] offers the advantage of allowing direct computation of the controller parameters from the parameters of Equation 1, the discrete model, provided that the estimation sample time is the same as the control sample time. The algorithm equation is given by:

$$u_t = g_o e_t + g_1 e_{t-1} + g_2 e_{t-2} + h_1 u_{t-1} + h_2 u_{t-2} \tag{8}$$

with $g_o = Q/b_1 \quad g_1 = -a_1 Q/b_1 \quad g_2 = -a_2 Q/b_1$

$h_1 = (b_1 - b_2)/b_1 \quad h_2 = b_2/b_1$

where $Q = (1 - e^{-T/\beta})$ is a tuning parameter that determines the tightness of control. For this study, the value of $\beta = 2$ was chosen.

Aperiodic Input

It is of considerable interest to investigate the use of an aperiodic forcing function for the adaptive scheme because in many cases set-point changes do not occur often enough in the course of normal process operation. In this regulatory situation, it is desirable to hold process upsets to a minimum. At the same time, it must be realized that the process must be driven enough to excite all nodes of the system. Examination of some of the results of this study suggested that estimation could be accomplished by a series of two symmetric pulses, one up and one down, after which the set-point is returned to its normal operating value.

Dynamic Estimation

For the static estimator, the lower bound matrix D is set to zero. Under these conditions, the IV algorithm "remembers" all of the samples from the start and thus averages the up and down changes in the forcing function. By introduction of D elements, the memory of the algorithm is shortened accordingly and the estimator can be made to track the parameter values associated with the latest change in set-point. This tracking may be more

desirable for a particular application than the average result obtained with $D = 0$. This point is illustrated in Figure 2 for the PID controller and in Figure 3 for the adaptive strategy employing the Dahlin control algorithm. These diagrams also show the effect of a step disturbance added at the 200th sample instant.

Figure 2 shows the effect of the aperiodic test input on the estimation of parameter b_1 which is proportional to the process gain. The initial parameters for these figures were obtained from the results of the static estimator. In the present case, P_o was chosen to be zero which indicates that the parameters are known to be accurate. For the static estimator (i.e., $D = \underline{0}$) $P_o = 0$ freezes the estimates regardless of any system inputs or disturbances. However, with nonzero elements in D, the algorithm is free to track even with $P_o = 0$. The diagonal elements of D were chosen to be the corresponding final values of the weighting matrix from static estimator runs. Following the aperiodic input, the set point is first increased by 2°F and the controller responds by reducing the cooling water rate u_t. The estimator correctly predicts that the process gain has increased and this is reflected by the increase in absolute value of the parameter b_1. In other words, the estimator was initialized with the "average" model and correctly tracked the parameter values for a set-point increase from the new information received. The other two steps of the aperiodic input follow the same reasoning. The initial values of the controller settings for the adaptive and the non-adaptive controllers were the same. These values were obtained from the Dahlin control law using the initial parameter set.

The desire to maintain a stable estimation algorithm in the face of large and abrupt load changes is generally in opposition with the desire to track system parameters. This subject is introduced here to point out the consideration that must be taken for the selection of the D matrix. At the 200th sample, the flow of reactants to the reactor was changed from $F = 16.7$ to $F = 15.0$ ft^3/min. Figures 2 and 3 illustrate this disturbance and its effects for the adaptive and the non-adaptive systems. The important result of this experiment is that the dynamic estimation algorithm remains stable for the adaptive configuration even with abrupt load changes. It is conceded that much work remains to be done in this area, but at the same time, it is felt that results presented here indicate that the dynamic IV estimation approach holds considerable promise.

SUMMARY AND CONCLUSION

This paper has dealt with the all important feature of an on-line estimation method applied in the process industry - that it be capable of representing non-linear dynamics with low-order linear models. An application to a jacketed chemical reactor was presented with a discussion on the specific non-linear behavior. While the open-loop estimation performance was found to be relatively independent of the amplitude of the forcing function, the closed-loop performance was shown to be more sensitive to input amplitude, but for this example application, the difference was not significant. Finally, evidence was given that the closed-loop reactor system could be estimated by use of an aperiodic test pulse used to minimize disturbance to the system.

ACKNOWLEDGEMENT

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NOTATION

A	reactor heat transfer area, sq. ft.
a	model output parameters
b	model input parameters
C	model bias parameter
C_A	reactant concentration, lb/cu. ft.
C_{AO}	inlet reactant concentration, lb/cu. ft.
C_p	specific heat, Btu/lb °F
D	lower bound matrix (5x5)
E	activation energy, °R
e	control algorithm error, °F
F	reactant flow rate, cu. ft/min.
ΔH	heat of reaction, Btu/lb
K_c	controller gain
k	reaction rate coefficient, cu. ft./lb-min.
k_o	reaction rate parameter, cu. ft./lb-min.
M	dead-time
M_c	jacket mass, lb or Btu/°F
P	weighting matrix (5x5)
Q	Dahlin controller parameter
R	control set-point, °F
T	sample time, min.
T_c	jacket temperature, °F
T_d	controller derivative time, min.
T_i	controller integral time, min.
T_o	reactant inlet temperature, °F
T_R	reactor temperature, °F
T_w	water inlet temperature, °F
t	time, min, time index
U	heat transfer coefficient, Btu/min-sq. ft. °F
u	input (deviation) variable, lbs/min.
V	reactor hold up, cu. ft.
W_c	cooling water rate, lbs/min
X	input signal amplitude, lbs/min
x	vector of endogeneous variables, (5x1)
y	output (deviation) variable, °F
z	vector of instrumental variables (5x1)
β	Dahlin closed-loop time constant, min.
λ	input signal period
φ	vector of model parameters (1x5)
ξ	model output variable, °F
ρ	reactant density, lb/cu. ft.

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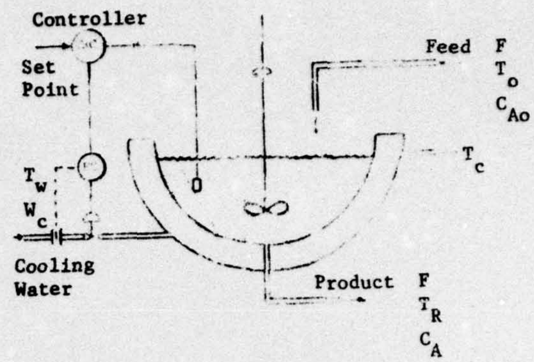

Figure 1. The Jacketed Chemical Reactor

Table I
Process Equations

Mass Balance on Reactant A

$$\frac{dC_A}{dt} = \frac{F}{V}(C_{Ao}-C_A) - kC_A^2$$

$$k = k_o \exp\left[\frac{-E}{(T_R + 460)}\right]$$

Energy Balance on Reacting Mixture

$$\frac{dT_R}{dt} = \frac{F}{V}(T_o-T_R) - \frac{UA}{\rho V C_p}(T_R-T_c) + \frac{\Delta H}{\rho C_p} kC_A^2$$

Energy Balance on Cooling Water

$$\frac{dT_c}{dt} = \frac{UA}{M_c}(T_R-T_c) - \frac{W_c}{M_c}(T_c-T_w)$$

Table II
Initial Conditions and System Parameters

Initial Conditions

$C_A = 3.6$ lbs/ft^3

$T_R = 190$°F

$T_c = 120$°F

System Parameters

$C_{Ao} = 9$ lbs/ft^3	$W_c = 1074$ lbs/min
$F = 16.7$ ft^3/min	$T_w = 80$°F
$\Delta H = 870$ Btu/lb	$C_p = 0.9$ Btu/lb-°F
$V = 250$ ft^3	$UA = 600$ Btu/min-°F
$T_o = 150$°F	$E = 2560$°R
$\rho = 60$ lbs/ft^3	$k_o = 1.43$ ft^3/lb-min
$M_c = 6000$ Btu/°F	

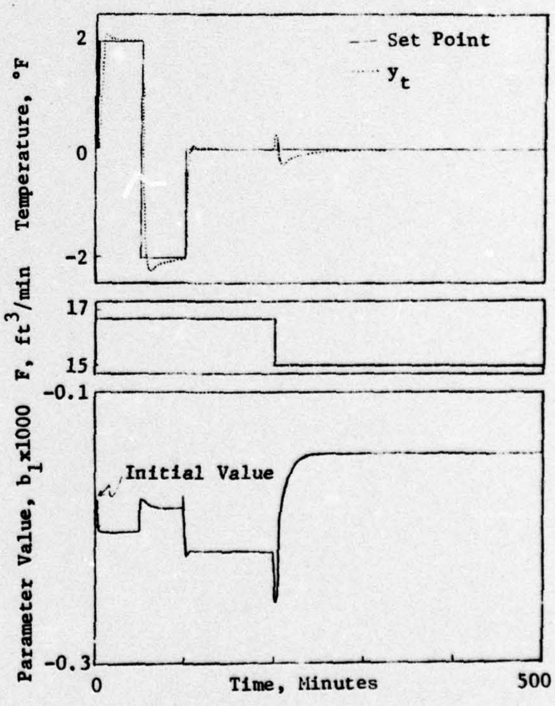

Figure 2. Time series showing the effect of an aperiodic set point function and a step disturbance on the dynamic IV estimation of parameter b_1 for the PID controller

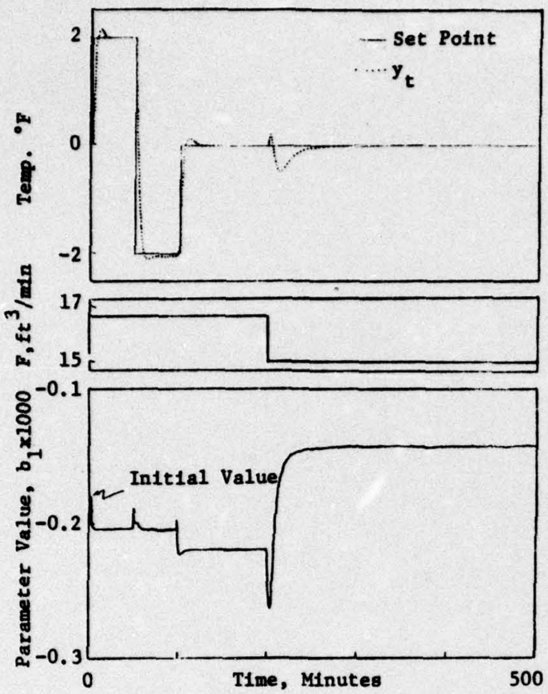

Figure 3. Time series showing the effect of an aperiodic set point function and a step disturbance on the dynamic IV estimation of parameter b_1 for the adaptive configuration

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This paper presents the use of computer simulation to test the application of the instrumental-variable method of process identification to the adaptive temperature control of a chemical reactor. The method is shown to be stable when used in a closed-loop configuration to update the parameters of a discrete linear model of the reactor. The updated parameters are used to adjust the parameters of a feedback control algorithm. Dynamic information is generated by aperiodic changes in control set-point. Unmeasured disturbances are shown to deteriorate the parameter estimates, but without catastrophic effects.

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